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Title: LUNA Condition-Based Monitoring Update: Dimensions and Sensors for Separating Act-Act from Act-Val and Differentiating Damage Types

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LUNA Condition-Based Monitoring Update:

Dimensions and Sensors for Separating Act-Act from Act-Val and Differentiating Damage Types

Andre Green

Classification Accuracy | **Damage & Actuator**

Predicting Damage Type [6 types]

Fold (1/9) | RF: 1.0 | MHL: 0.98
Fold (2/9) | RF: 1.0 | MHL: 0.99
Fold (3/9) | RF: 0.96 | MHL: 0.99
Fold (4/9) | RF: 0.98 | MHL: 0.99
Fold (5/9) | RF: 0.98 | MHL: 0.99
Fold (6/9) | RF: 0.99 | MHL: 0.99
Fold (7/9) | RF: 0.96 | MHL: 0.99
Fold (8/9) | RF: 0.98 | MHL: 0.99
Fold (9/9) | RF: 0.97 | MHL: 0.97

Tech.	MIN	MED	MAX
RF	0.96	**0.98**	1.0
MHL	0.97	**0.99**	0.99

Predicting Actuator [Act-Act vs. Act-Valve]

Fold (1/9) | RF: 1.0 | MHL: 1.0
Fold (2/9) | RF: 1.0 | MHL: 1.0
Fold (3/9) | RF: 1.0 | MHL: 1.0
Fold (4/9) | RF: 1.0 | MHL: 1.0
Fold (5/9) | RF: 1.0 | MHL: 1.0
Fold (6/9) | RF: 1.0 | MHL: 1.0
Fold (7/9) | RF: 1.0 | MHL: 1.0
Fold (8/9) | RF: 1.0 | MHL: 1.0
Fold (9/9) | RF: 1.0 | MHL: 1.0

Tech.	MIN	MED	MAX
RF	1.0	**1.0**	1.0
MHL	1.0	**1.0**	1.0

These results are suspiciously good; both the Mahalanobis Ensemble and the Random Forest get 100% accuracy (in every fold) differentiating Act-Act from Act-Valve.

The following 3 variables very easily separate Act-Act and Act-Valve:

- Mean of PG3
- Variance of PG3
- Difference in Temperature Variance

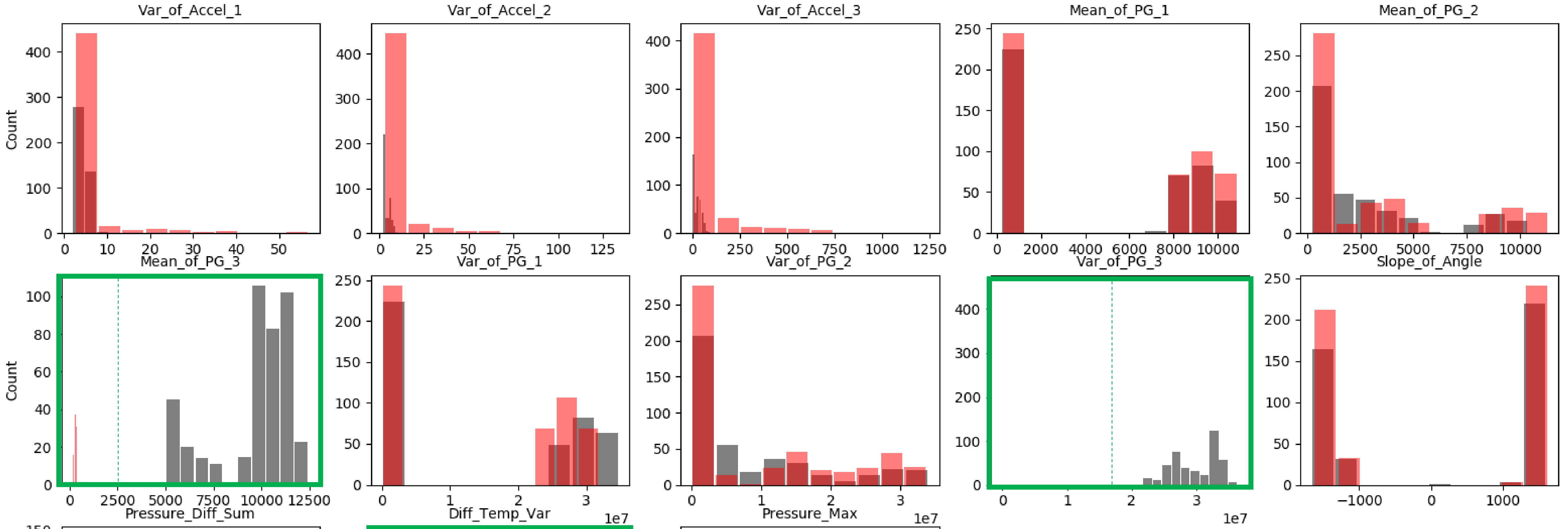
Specifically, the mean of PG3 is almost 0 for all of the Act-Val samples, and ranges from 5,000-12,500 for Act-Act.

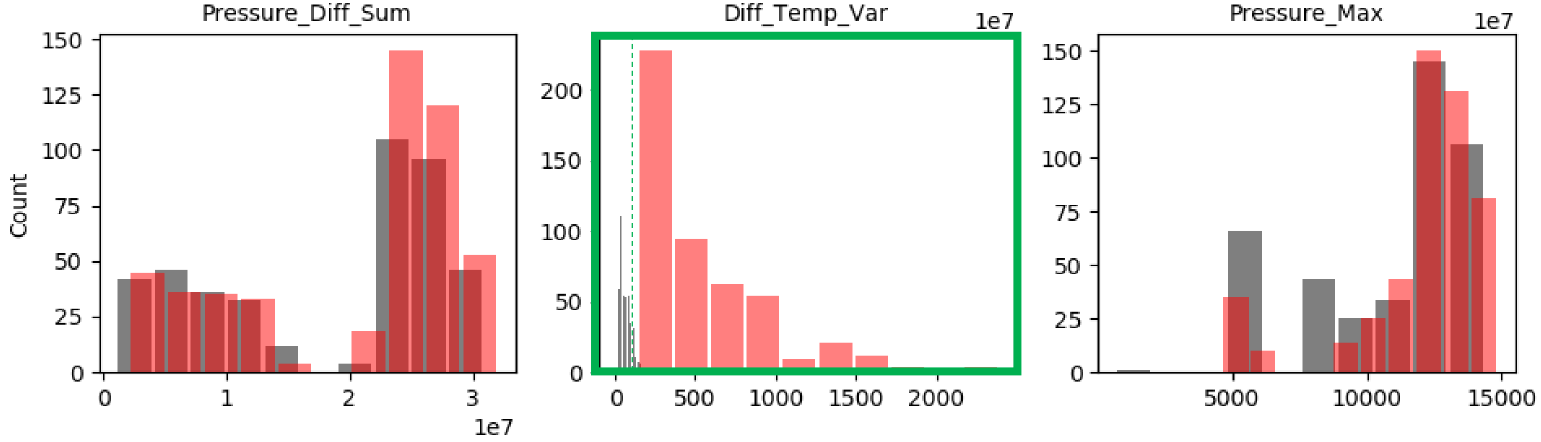
Likewise, the variance of PG3 is again almost 0 always 0 for Act-Val.

Finally, the 'Diff_Temp_Var' is almost always 0 for Act-Act, but ranges from 250-2,000 for Act-Val.

Ali Feature Histograms | **Actuator vs. Damage Dataset**

RED: Act-Val | BLACK: Act-Act

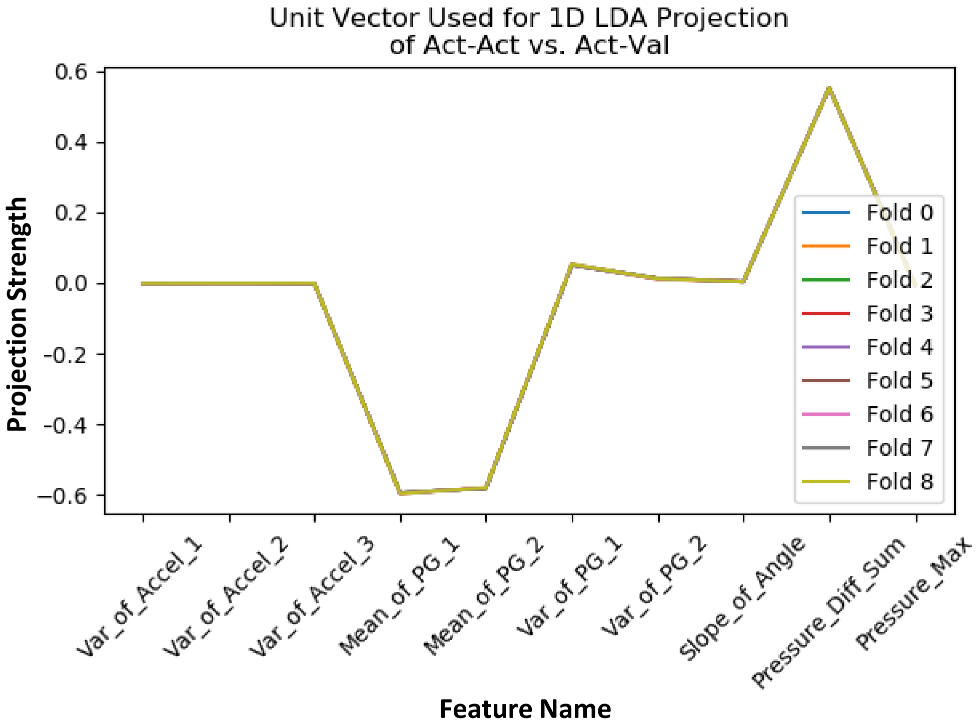




Mean of PG3, Var of PG_3, and Diff_Temp_Var (bordered in green) clearly split Act-Act from Act-Val.

Act-Act doesn't appear on the PG3 variance histogram because the values are so tightly grouped (i.e. the bars are so thin) relative to the range of the graph that they're not rendered at this scale. Zooming in shows that the Act-Act values are all very close to 0.

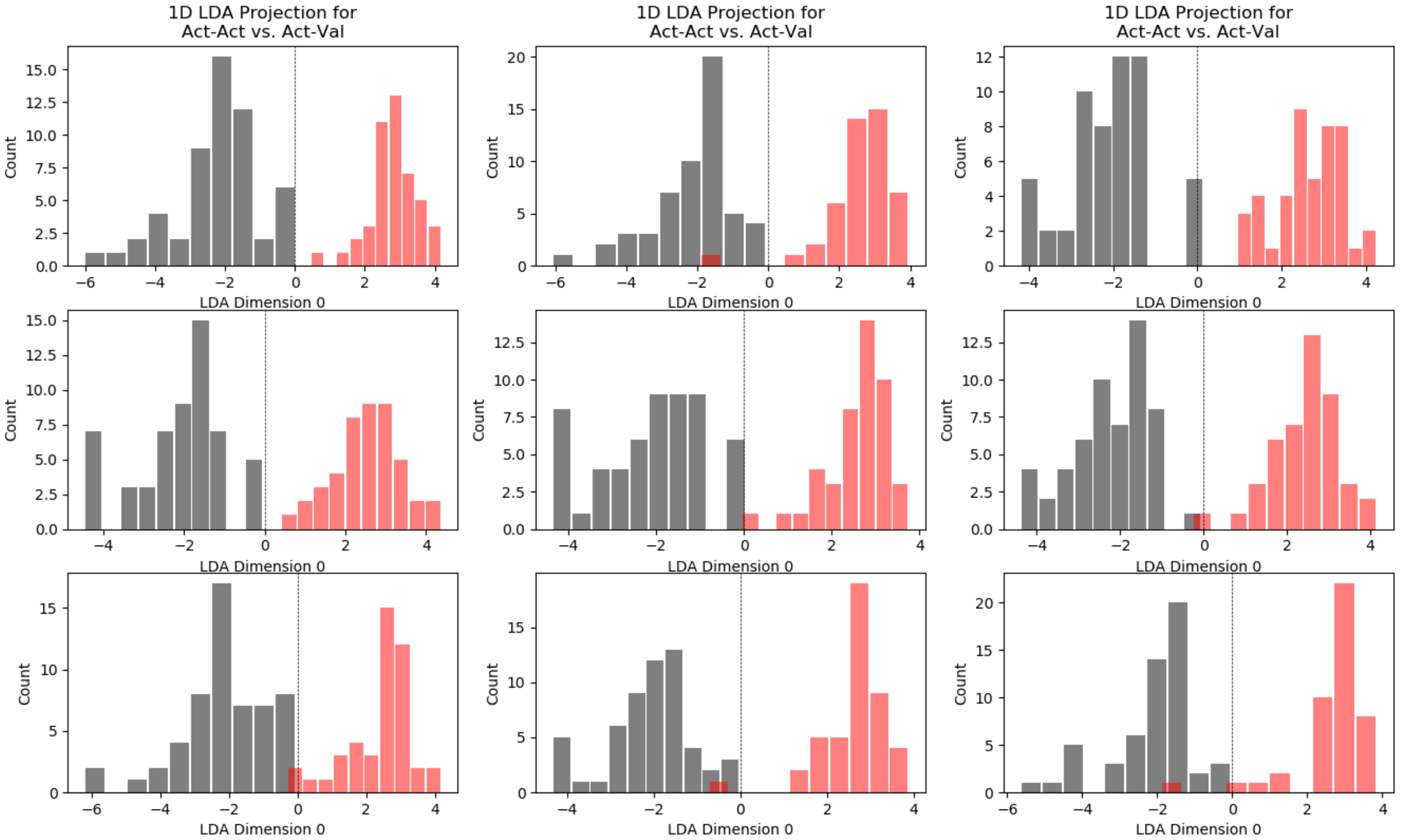
LDA for Separating Actuators | **Linear Separation Imperfect**



LDA Projection Direction Unit Vector [9th fold]

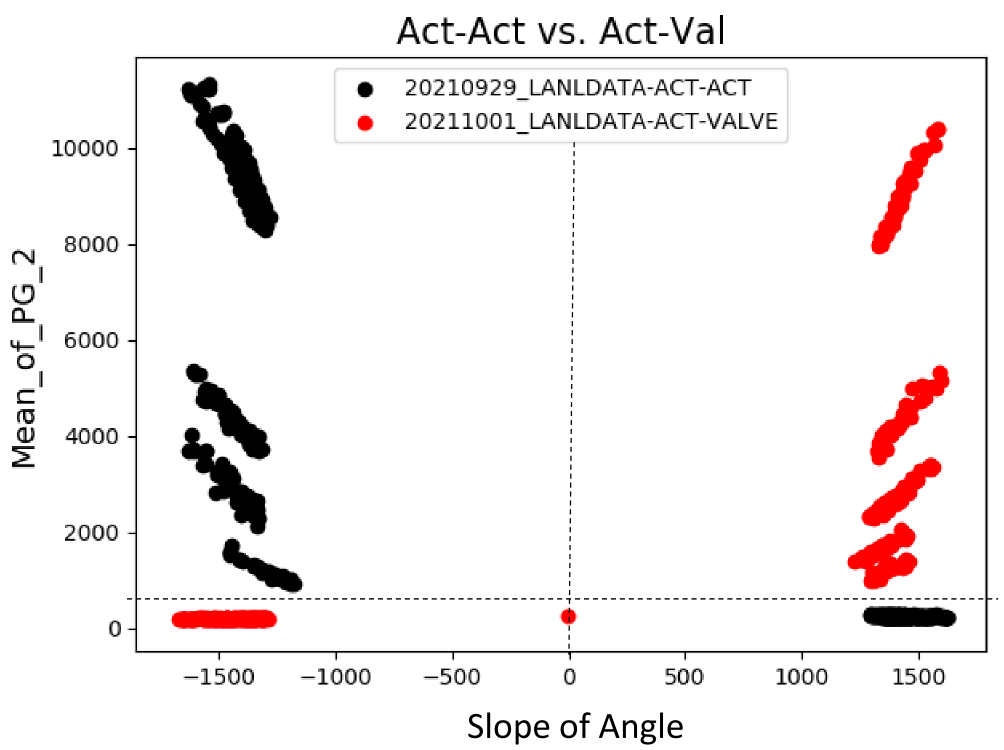
Var_of_Accel_1	-0.002
Var_of_Accel_2	-0.001
Var_of_Accel_3	-0.001
Mean_of_PG_1	**-0.596**
Mean_of_PG_2	**-0.580**
Var_of_PG_1	0.053
Var_of_PG_2	0.012
Slope_of_Angle	0.004
Pressure_Diff_Sum	**0.552**
Pressure_Max	-0.006

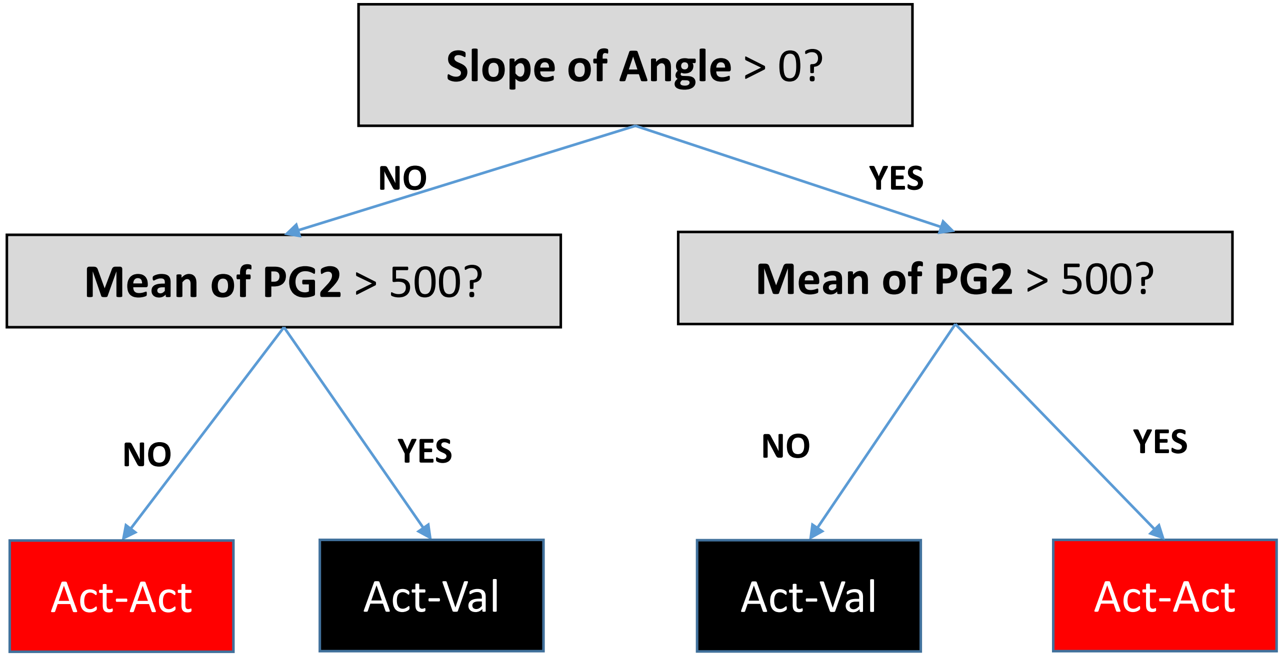
Although only the LDA-chosen dimension for the 9th fold is written above, the plot above shows the LDA dimension chosen for each fold is practically the same every time.



Above: The histograms show the counts for each class (Act-Act vs. Act-Val) when projected along the LDA-chosen direction vector for each of the 9 folds in the 9-fold stratified cross validation. The LDA-chosen direction vector does a reasonable job of separating the two, but isn't perfect. Conveniently, the LDA sensors used for separating Act-Act from Act-Val are a subset of the sensors which work best for separating the damage types.

Tree for Separating Actuators | **Non-Linear Separation Perfect**





In this 2D projection, it's trivial for a Random Forest (or even just a decision tree) to separate Act-Act from Act-Val.

However, it's still difficult for a simple linear classifier (there is no single line separating the two) and for the MHL classifier (the data are not Gaussian-Distributed in this space). Even using a parabolic kernel, it appears the cross-section of the surface would need to be almost L-shaped.

Above: An simple decision tree that would separate the two actuators from each other. As is evidenced in the graph on the left (and ignoring the point at Slope_of_Angle == 0) there's a large margin on the values picked for dividing the space.

Classification Accuracy | **Damage & Actuator** | Reduced Feature Set

Predicting Damage Type [6 types]

Fold (1/9) | RF: 0.93 | MHL: 0.9
Fold (2/9) | RF: 0.99 | MHL: 0.94
Fold (3/9) | RF: 0.99 | MHL: 0.96
Fold (4/9) | RF: 0.98 | MHL: 0.93
Fold (5/9) | RF: 0.97 | MHL: 0.95
Fold (6/9) | RF: 0.98 | MHL: 0.94
Fold (7/9) | RF: 0.96 | MHL: 0.94
Fold (8/9) | RF: 0.96 | MHL: 0.93
Fold (9/9) | RF: 0.98 | MHL: 0.88

Tech.	MIN	MED	MAX
RF	0.93	**0.97**	0.99
MHL	0.88	**0.93**	0.96

There is virtually no impact on the accuracy results for damage type prediction having removed PG3 and Diff_Temp_Var.

The random forest used 10 trees with a maximum depth of 12.

Predicting Actuator [Act-Act vs. Act-Valve]

Fold (1/9) | RF: 1.0 | MHL: 1.0
Fold (2/9) | RF: 1.0 | MHL: 0.99
Fold (3/9) | RF: 1.0 | MHL: 1.0
Fold (4/9) | RF: 1.0 | MHL: 1.0
Fold (5/9) | RF: 0.99 | MHL: 1.0
Fold (6/9) | RF: 1.0 | MHL: 1.0
Fold (7/9) | RF: 1.0 | MHL: 0.99
Fold (8/9) | RF: 1.0 | MHL: 1.0
Fold (9/9) | RF: 1.0 | MHL: 1.0

Tech.	MIN	MED	MAX
RF	0.99	**1.0**	1.0
MHL	0.99	**1.0**	1.0

Act-Act and Act-Val can still be very well separated without the use of PG3 and Diff_Temp_Var.

The three variables that seemed suspiciously well-separated have been removed (PG3’s mean, PG3’s variance, and Diff_Temp_Var), because they may have been a result of sensor malfunction.

Only the following features were used for these results:

Var_of_Accel_1, Var_of_Accel_2 Var_of_Accel_3, Mean_of_PG_1, Mean_of_PG_2, Var_of_PG_1, Var_of_PG_2, Slope_of_Angle, Pressure_Diff_Sum, Pressure_Max

10 features, 5 damage types, 2 actuators.

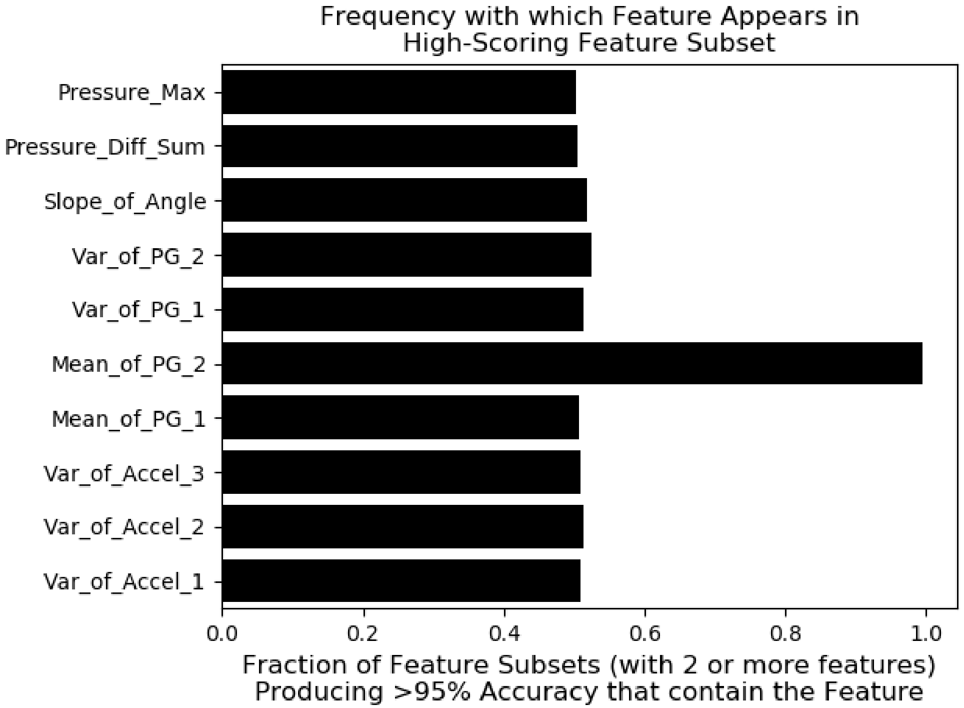
Scores for Subsets | **Random Forest**

5 damage types: [Baseline, Baseline_300, Eleak_005, Eleak_010, Eleak_050]
10 features: ['Var_of_Accel_1' 'Var_of_Accel_2' 'Var_of_Accel_3' 'Mean_of_PG_1' 'Mean_of_PG_2' 'Var_of_PG_1' 'Var_of_PG_2' 'Slope_of_Angle' 'Pressure_Diff_Sum' 'Pressure_Max']

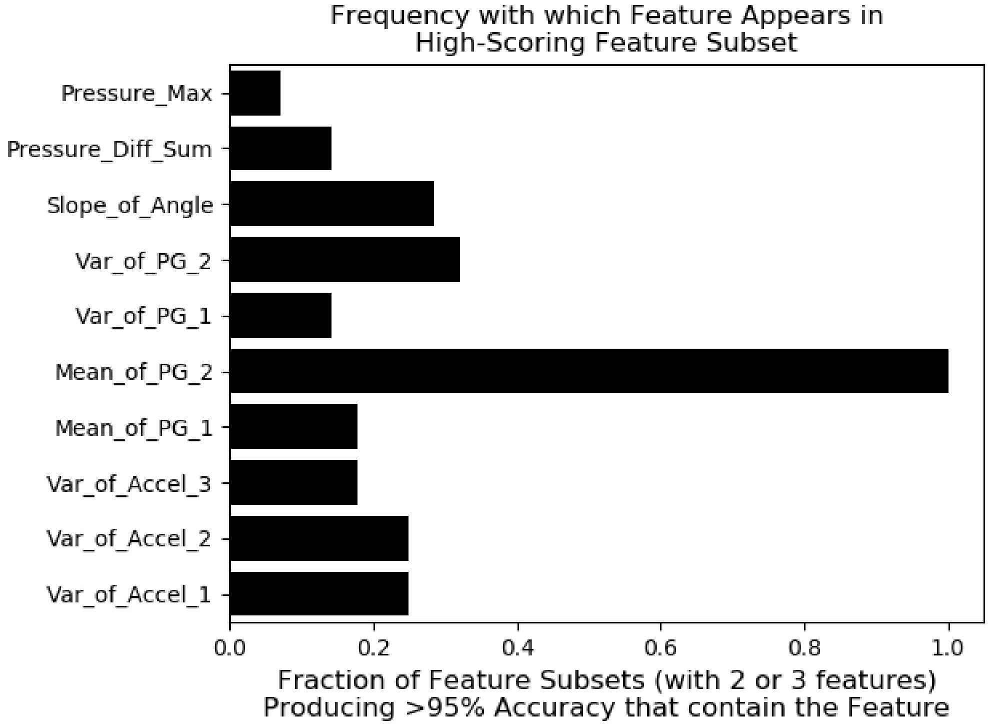
The random forest used 10 trees with a maximum depth of 12.

Features*	Median Score
(4, 6, 7)	0.98
(2, 4, 7)	0.97
(4, 5, 6)	0.97
(3, 4, 6)	0.97
(4, 6, 9)	0.97
(1, 2, 4)	0.96
(1, 4, 6)	0.96
(0, 4, 6)	0.96
(1, 4)	**0.96**
(4, 6, 8)	0.96
(4, 7, 8)	0.96
(4, 7, 9)	0.96
(3, 4, 5)	0.96
(0, 3, 4)	0.96
(0, 2, 4)	0.96
(2, 4, 6)	0.96
(1, 3, 4)	0.96
(1, 4, 7)	0.96
(4, 6)	**0.96**
(4, 7)	**0.95**
(3, 4, 7)	0.95
(0, 4, 5)	0.95
(1, 4, 8)	0.95
(1, 4, 5)	0.95
(2, 4)	**0.95**
(0, 4)	**0.95**
(0, 4, 8)	0.95
(0, 4, 7)	0.95

***Only the feature subsets with 3 or fewer features are shown here,** but for the histograms, all combinations of feature subsets with more than 2 features [1,000+ subsets] were tested.*



The histogram above shows the fraction of feature subsets scoring above 95% which contain a given feature; e.g. Mean_of_PG2 is included in 98%-99% of all subsets which score above 95% accurate [median over 9-fold stratified cross-validation].



The histogram above shows the fraction of feature subsets with 2 or 3 features scoring above 95% which contain a given feature. Mean_of_PG2 appears in all of them. The only subsets which perform well (>95% accuracy) and do not include this feature have 4 or more other features.

This makes sense: The damage type is Eleak, so that a pressure gauge is useful in determining the type/severity of damage is not surprising.

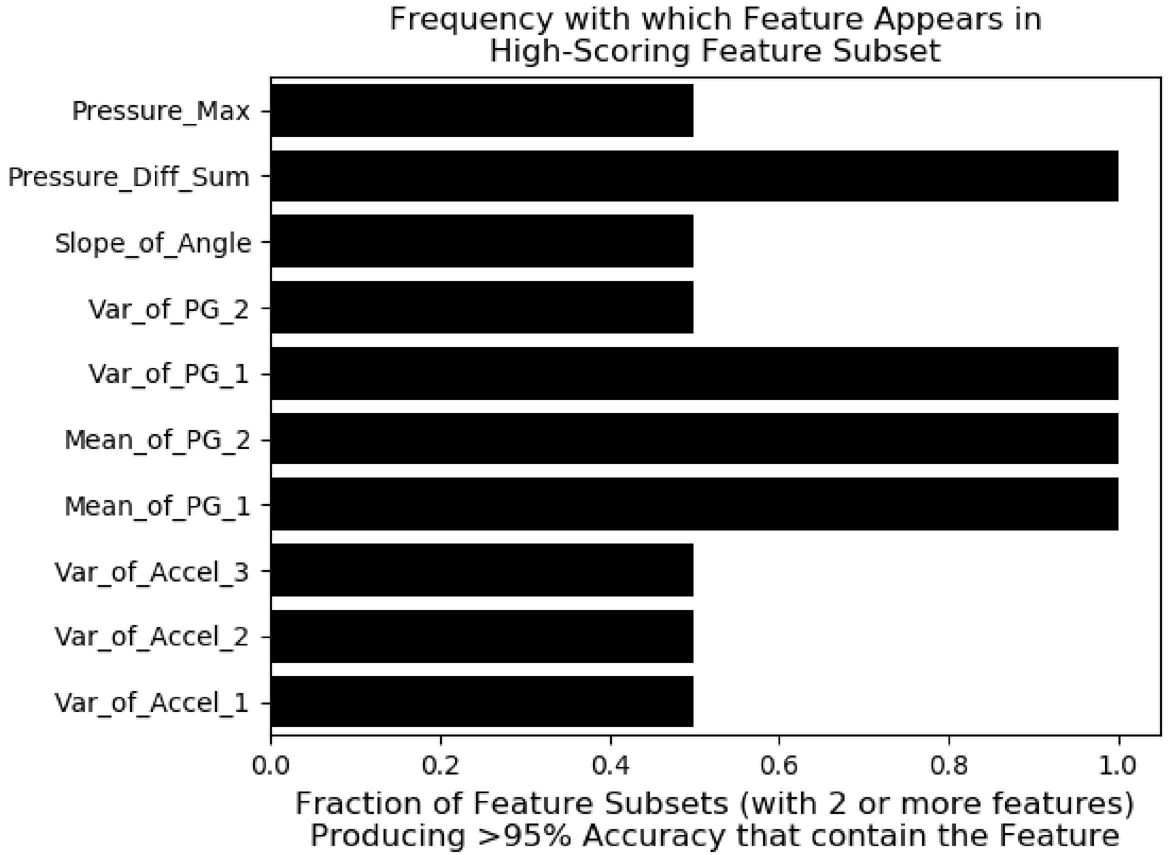
Scores for Subsets | **Mahalanobis Ensemble**

5 damage types: [Baseline, Baseline_300, Eleak_005, Eleak_010, Eleak_050]
10 features: ['Var_of_Accel_1' 'Var_of_Accel_2' 'Var_of_Accel_3' 'Mean_of_PG_1‘ 'Mean_of_PG_2' 'Var_of_PG_1' 'Var_of_PG_2' 'Slope_of_Angle' 'Pressure_Diff_Sum' 'Pressure_Max']

Features	Median Accuracy
(0, 1, 2, 3, 4, 5, 6, 7, 8, 9)	0.94
(1, 2, 3, 4, 5, 6, 7, 8, 9)	0.94
(0, 3, 4, 5, 6, 7, 8, 9)	0.94
(1, 3, 4, 5, 6, 7, 8, 9)	0.94
(2, 3, 4, 5, 6, 7, 8, 9)	0.94
(3, 4, 5, 6, 7, 8, 9)	0.94
(0, 1, 3, 4, 5, 6, 7, 8, 9)	0.94
(0, 2, 3, 4, 5, 6, 7, 8, 9)	0.94

Mahalanobis has a much harder time with damage type classification using a reduced feature set, and does not ever get >95% median accuracy over 9-fold stratified cross-validation.

This is possibly because the data is not Gaussian (or even single-peak) distributed – e.g. it may be bimodal.

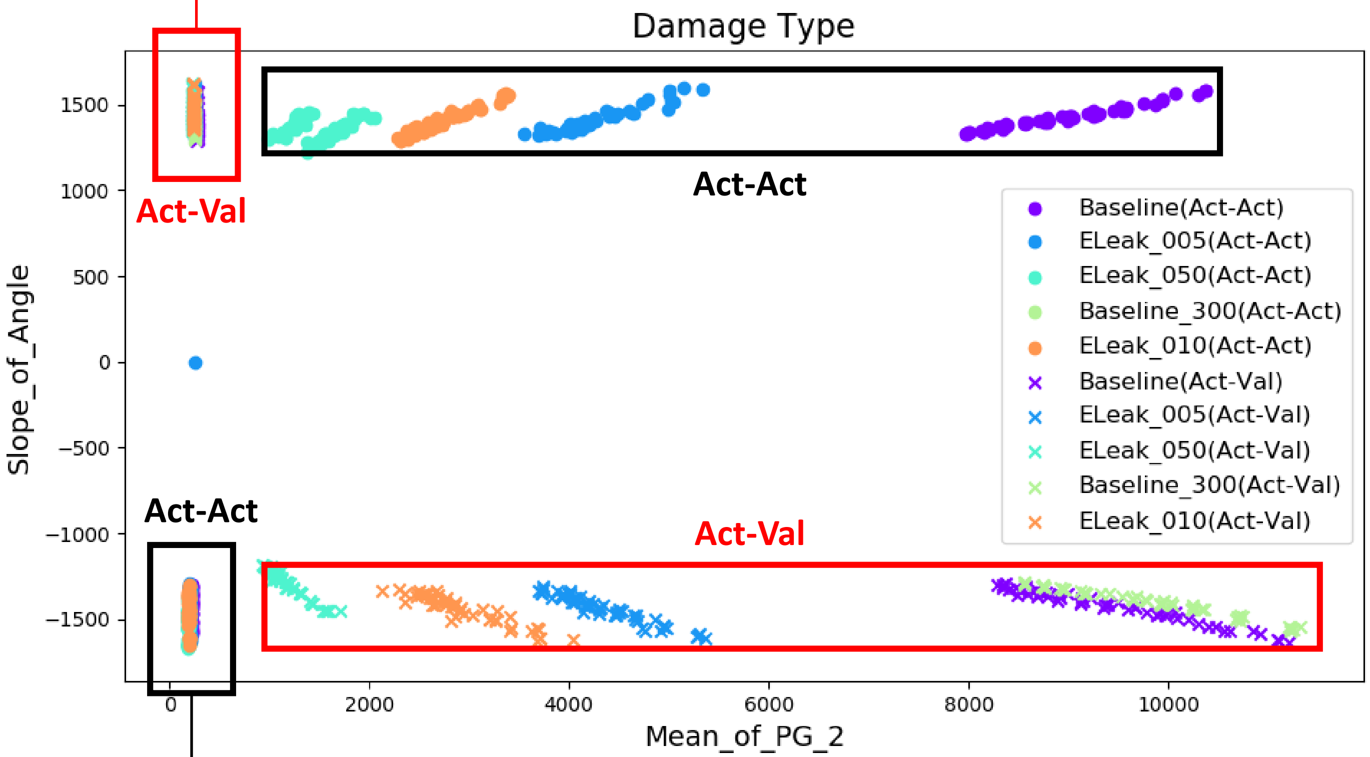


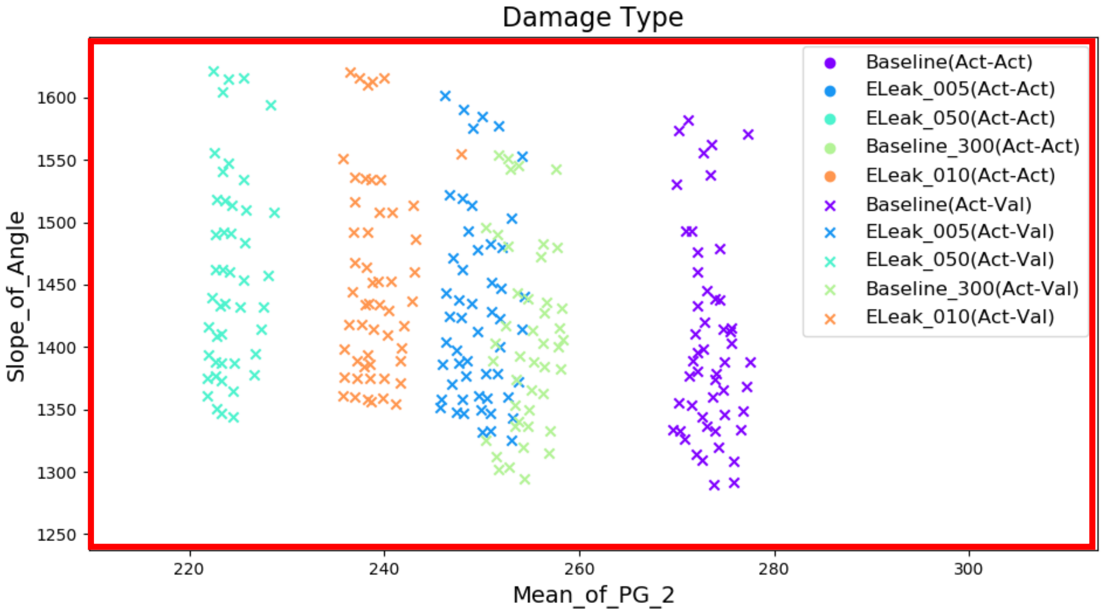
The histogram above shows the fraction of feature subsets scoring above 90% which contain a given feature; e.g. Pressure_Diff_Sum, Var. of PG1 and mean of PG2 & PG1 appear in every subset which scored at or above 90% accurate [median over 9-fold stratified cross-validation].

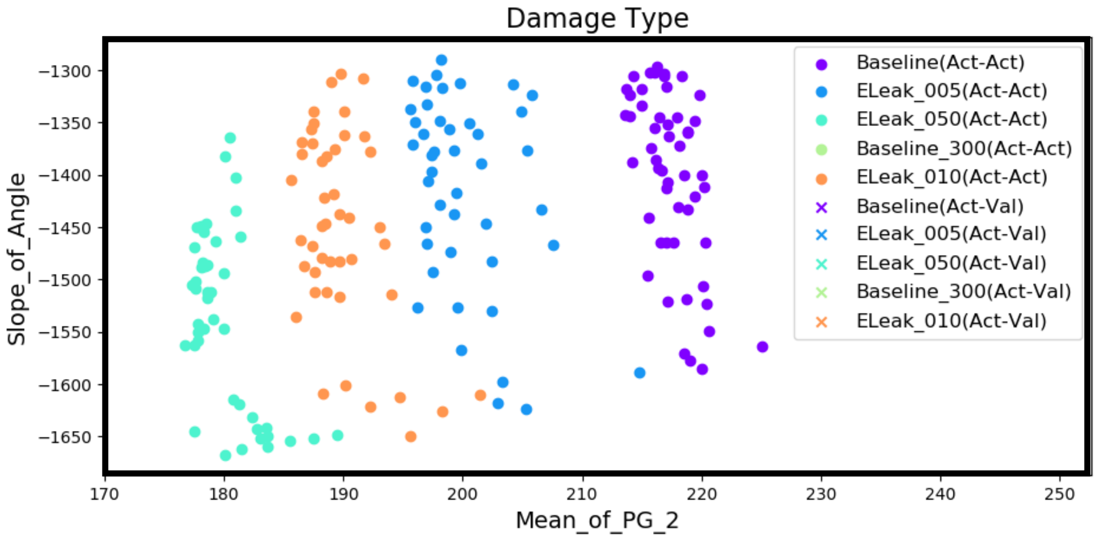
High-Scoring 2D Subspace: [4, 6] (96% accurate)| **Random Forest**

Color indicates damage type, and marker shape (**x** or **o**) differentiates Act-Act from Act-Val.

For positive rotations, Act-Act's damage-type subgroups have greater variance [and difference in means] along PG2 than they do for negative rotations.

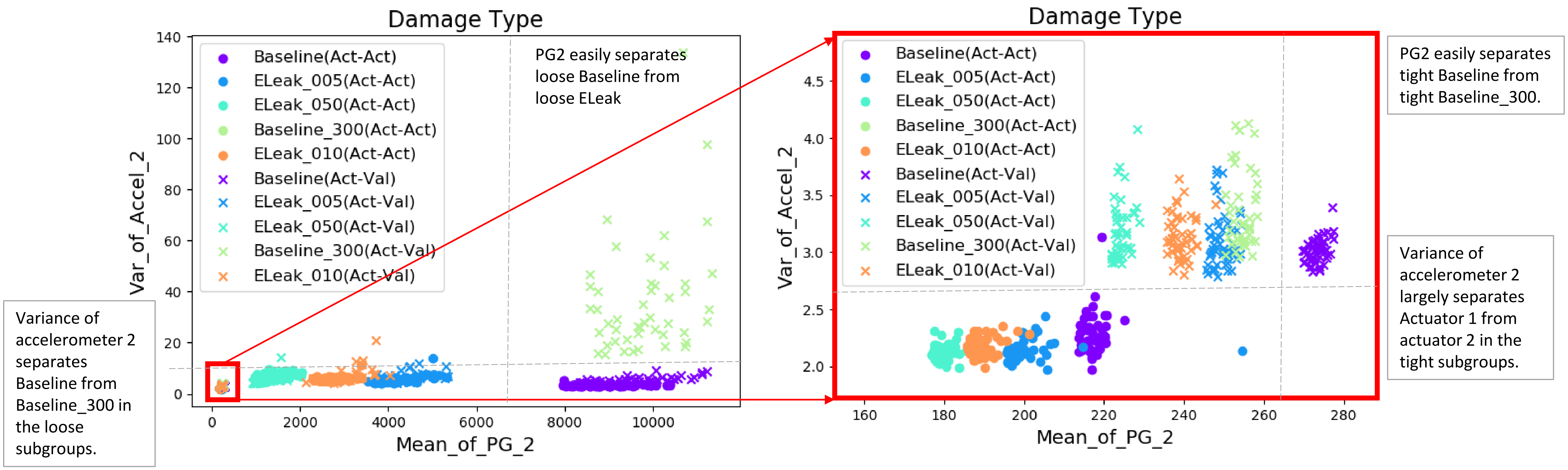






Act-Val exhibits the same behavior as Act-Act, but with the sensitivity to rotation reversed; variance in the groups and the difference between damage type group means is much larger for negative rotations than for positive.

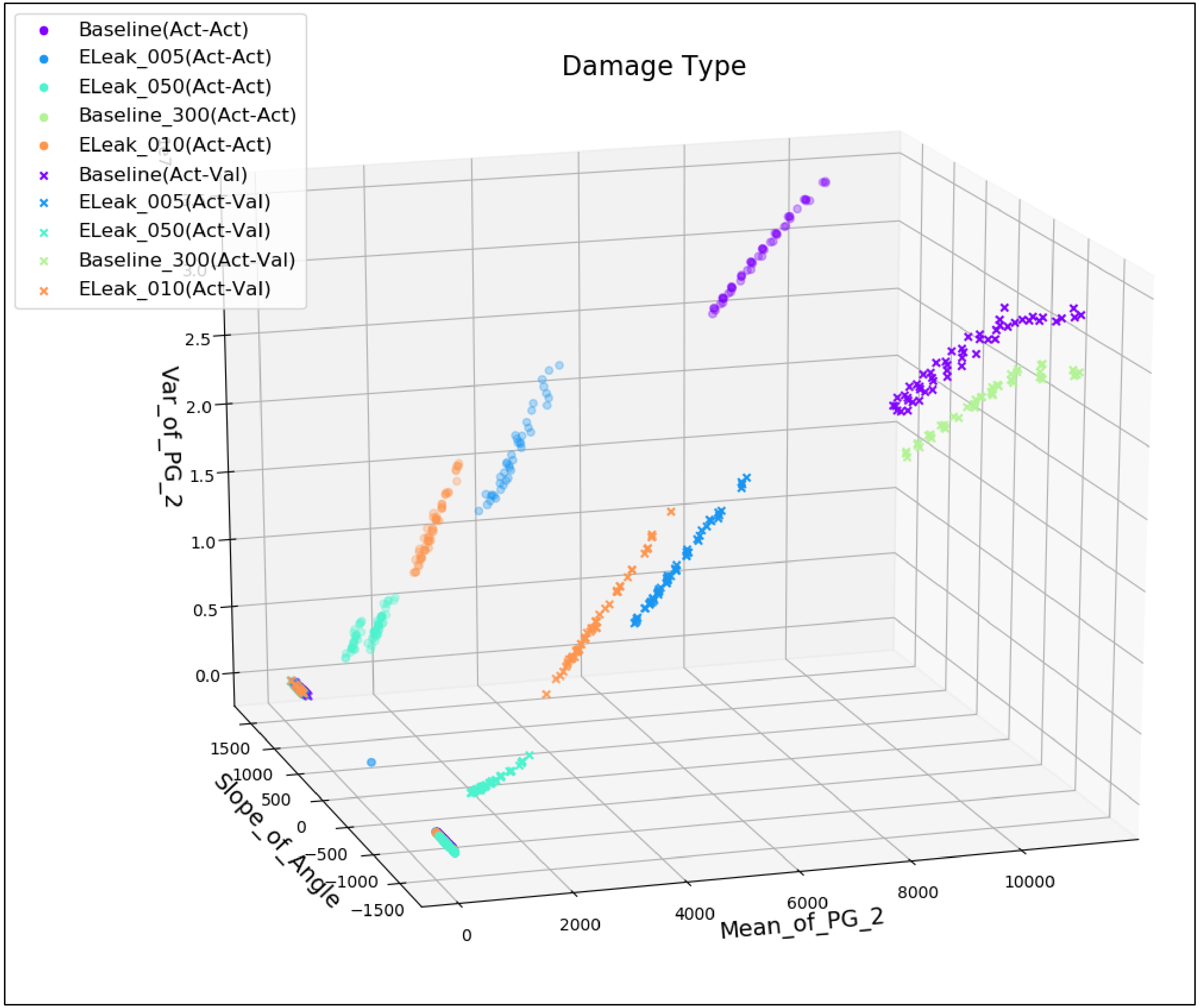
High-Scoring 2D Subspace: [1, 4] (96% accurate)| **Random Forest**



The two features of the best-scoring 2-feature subset (Mean_of_PG2 & Var_of_Accel_2) were used by the random forest to obtain a median score of 96% accuracy over 9-fold cross-validation. Interestingly, both actuators have sub-groups much more tightly grouped in PG2 which have similar kinds of relationships as those groups more spread out/loose in PG2.

However, the relationship between Baseline_300 and Baseline is markedly different between the tight and loose subgroups; for the tight subgroups, Baseline_300 and Baseline have clearly different PG2 means and Baseline_300 and Eleak_005 have similar PG2 means, whereas for the loose subgroups Baseline_300 and Baseline have similar PG2 means and very different Accel_2 variances and Baseline_300 and Eleak_005 have very different PG2 means.

Best-Scoring 3D Subspace: [4, 6, 7] (98% accurate)| **Random Forest**

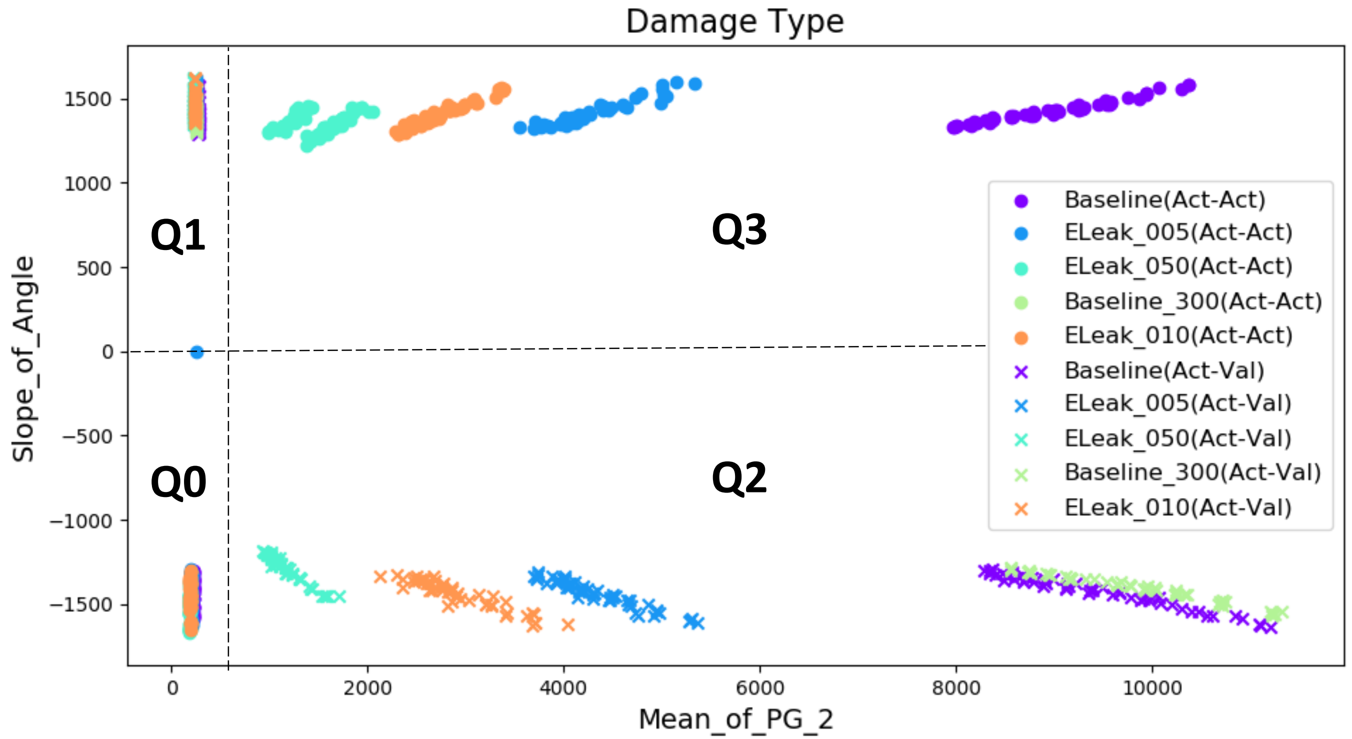


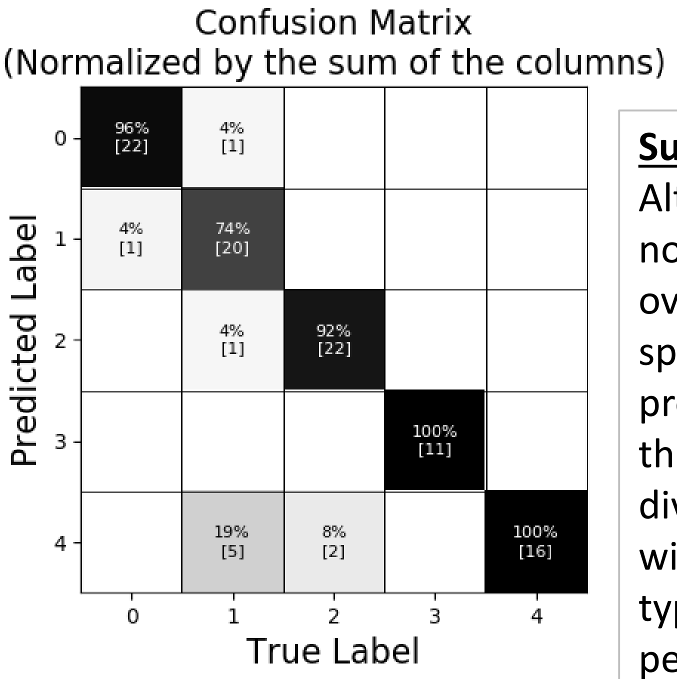
This subspace has largely separated each cluster, but there are still the sets of loosely and tightly grouped damage types.

The damage types are not Gaussian distributed and there is no single direction discoverable by LDA in which damage will change monotonically.

As a consequence of the non-Gaussian distribution (specifically that there are four blobs for each damage type with many other damage points lying in-between), the Mahalanobis ensemble will likely perform poorly.

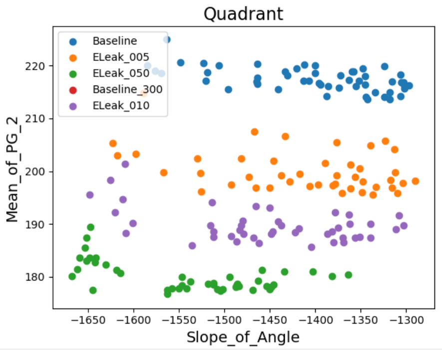
Dividing the Feature Space into Quadrants

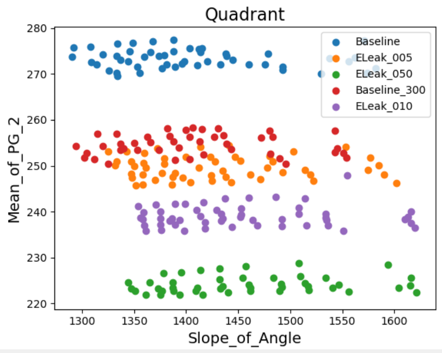


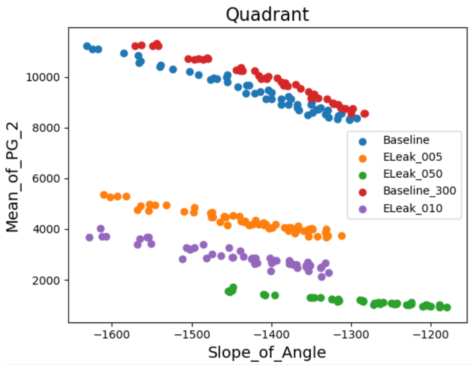


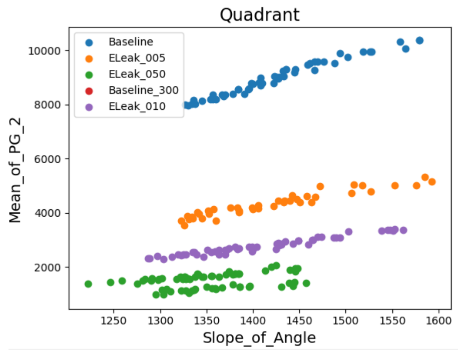
Subspace Distributions

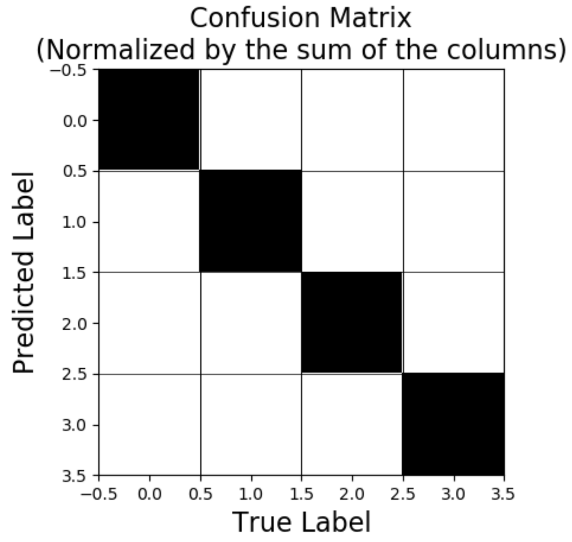
Although the points are not Gaussian distributed over the entire feature space, under this 2D projection it appears that the damage types can be divided into 4 quadrants within which the damage types are at least single-peak distributed.









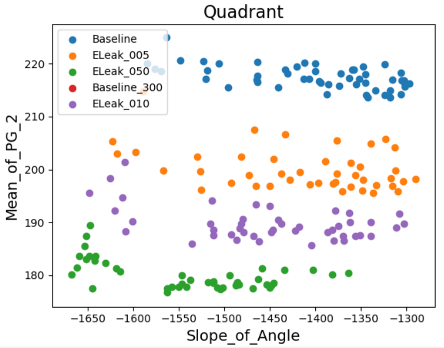


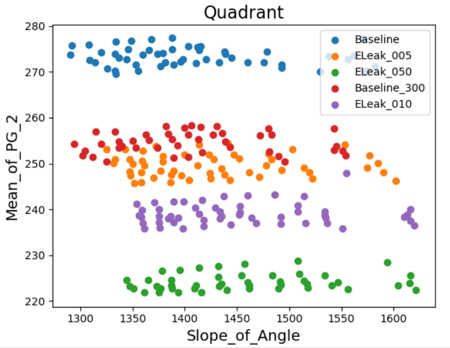
MHL on Quadrants

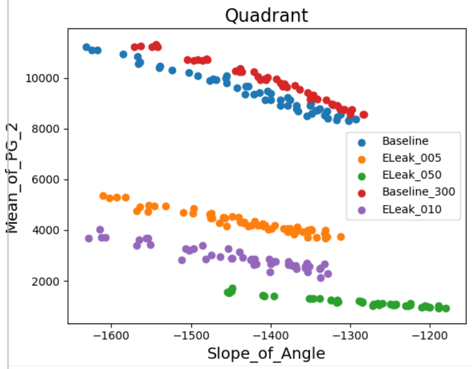
Applying the MHL ensemble to the quadrant individually produced perfect results for all quadrants on the first fold (full results for all folds on next slide). Projections of the points in each quadrant are shown in 2D, but the MHL ensemble used to obtain the perfect predictions [conf. mat shown on right] is currently using the full 10-D feature space.

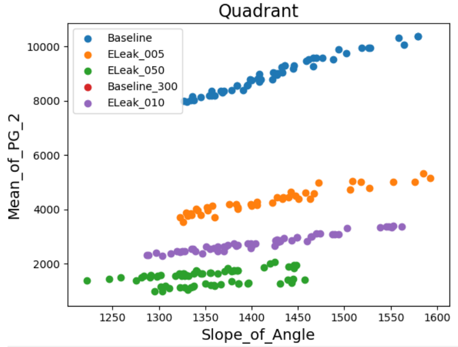
MHL on Quadrants, using all Features | **Mahalanobis Ensemble**

2D-Projection









3-Fold Cross Validation	Fold (0/3): 1.0 Fold (1/3): 0.98 Fold (2/3): 0.98 [0.98, 0.98, 1.0]	Fold (0/3): 1.0 Fold (1/3): 0.99 Fold (2/3): 1.0 [0.99, 1.0, 1.0]	Fold (0/3): 1.0 Fold (1/3): 1.0 Fold (2/3): 1.0 [1.0, 1.0, 1.0]	Fold (0/3): 1.0 Fold (1/3): 1.0 Fold (2/3): 1.0 [1.0, 1.0, 1.0]
9-Fold Cross Validation	Fold (0/9): 1.0 Fold (1/9): 1.0 Fold (2/9): 1.0 Fold (3/9): 0.95 Fold (4/9): 1.0 Fold (5/9): 1.0 Fold (6/9): 0.95 Fold (7/9): 1.0 Fold (8/9): 1.0 [0.95, 1.0, 1.0]	Fold (0/9): 1.0 Fold (1/9): 1.0 Fold (2/9): 1.0 Fold (3/9): 1.0 Fold (4/9): 1.0 Fold (5/9): 1.0 Fold (6/9): 1.0 Fold (7/9): 1.0 Fold (8/9): 1.0 [1.0, 1.0, 1.0]	Fold (0/9): 1.0 Fold (1/9): 1.0 Fold (2/9): 1.0 Fold (3/9): 1.0 Fold (4/9): 1.0 Fold (5/9): 1.0 Fold (6/9): 1.0 Fold (7/9): 1.0 Fold (8/9): 1.0 [1.0, 1.0, 1.0]	Fold (0/9): 1.0 Fold (1/9): 1.0 Fold (2/9): 1.0 Fold (3/9): 1.0 Fold (4/9): 1.0 Fold (5/9): 1.0 Fold (6/9): 1.0 Fold (7/9): 1.0 Fold (8/9): 1.0 [1.0, 1.0, 1.0]

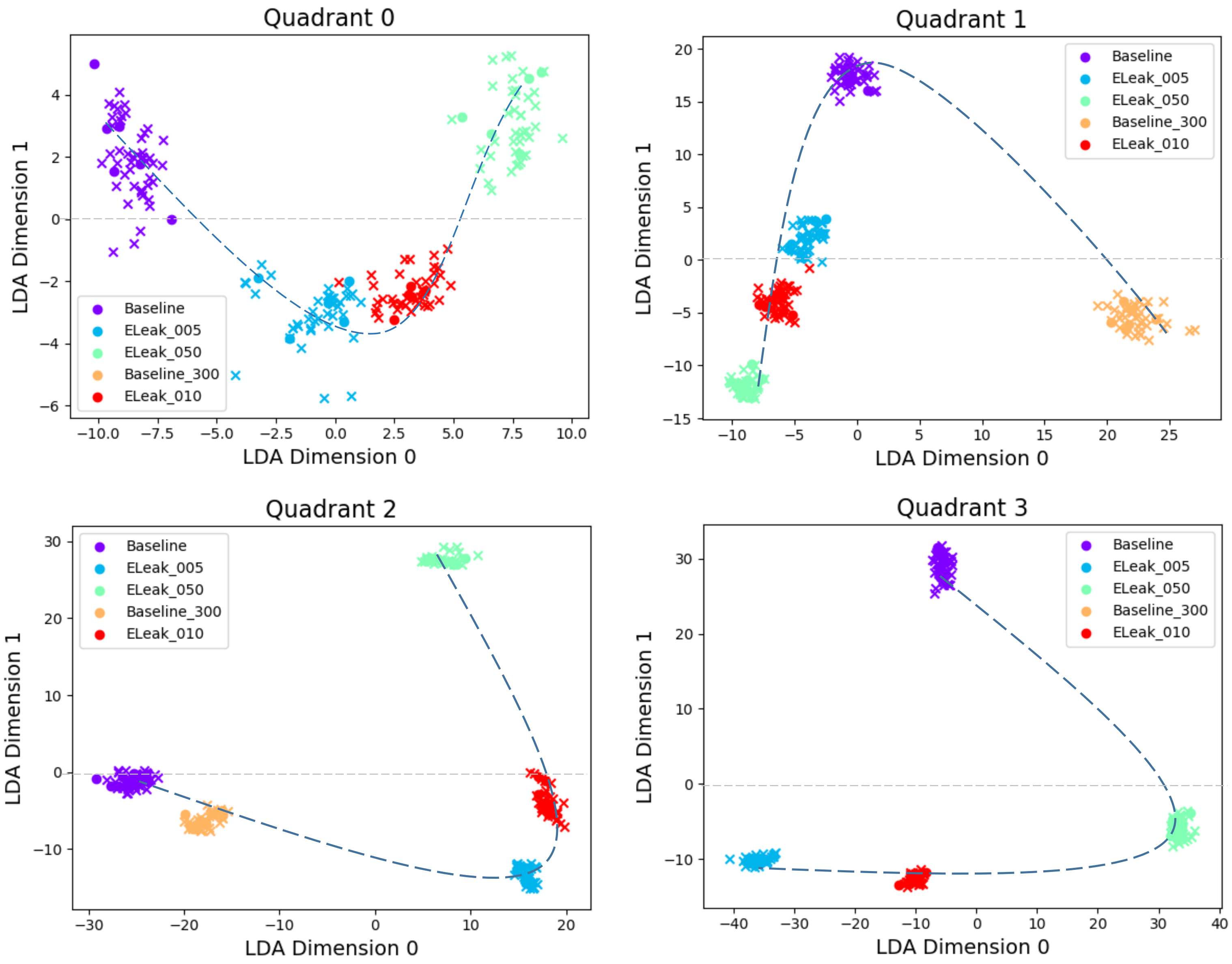
Dividing into quadrants greatly improved the performance of the MHL classifier (from 92% to >98%).

Because the regions were divided into quadrants, a test using fewer folds was conducted.

A high number of folds on a small dataset results in low granularity for expressing error; e.g. a single mistake may constitute a 5% reduction in measured accuracy)

There are two drawbacks to this method: 1. Currently, the regions had to be *manually* selected, and 2. the memory requirement for storing the MHL ensemble roughly quadruples.

LDA on Quadrants | **Non-Monotonicity**



Xs denote training points for LDA, Os are testing points for LDA. The polynomials are hand-drawn and are just approximations of possible curves to fit the means.

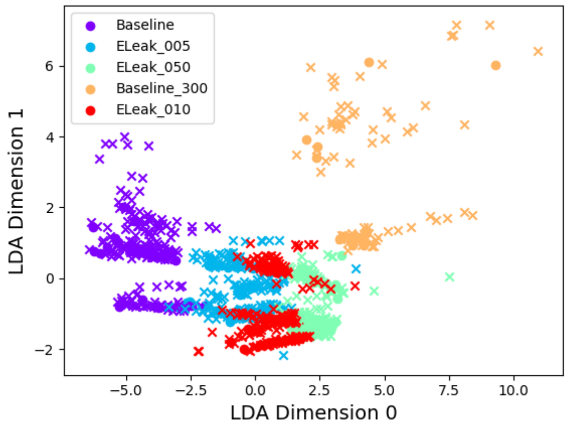
Monotonic over Polynomial Curves

Using 2D LDA on each quadrant produces largely separated groups, but linearly projecting (e.g. down to the x-axis) to a single axis does not produce a consistent monotonic ordering of damage.

In part this may be due to LDA not knowing that there's any desired ordering to the groups it separates.

It could also be that there is no straight-line direction [although there may be polynomials, as drawn in the figures on right] in the current feature subspace on to which the data can be projected while keeping the groups separate and monotonically ordered with respect to damage.

Finally, this may simply be because Eleak 005, 010, and 050 are a different type of damage from Baseline than Baseline 300 is.

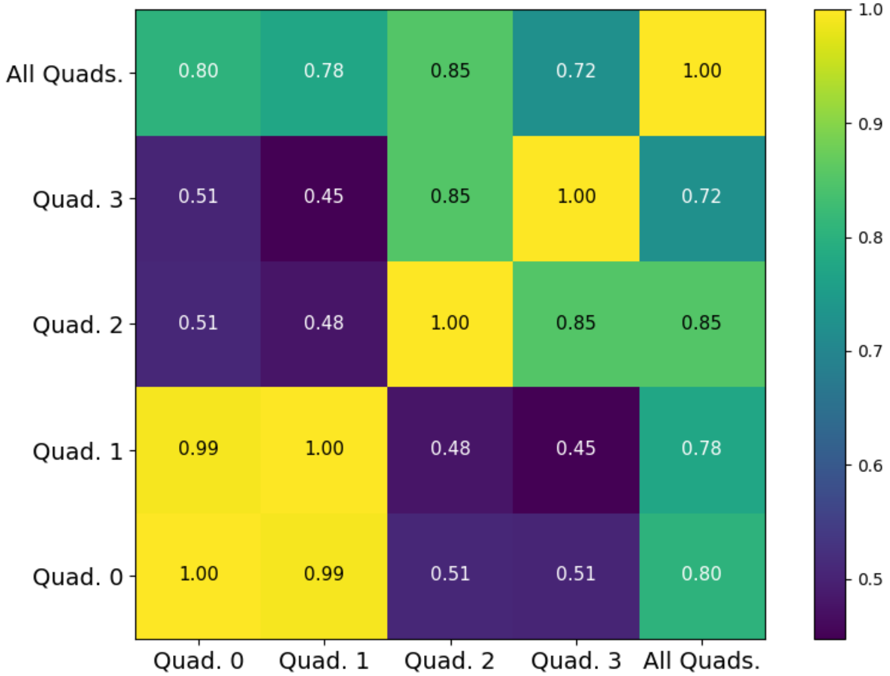


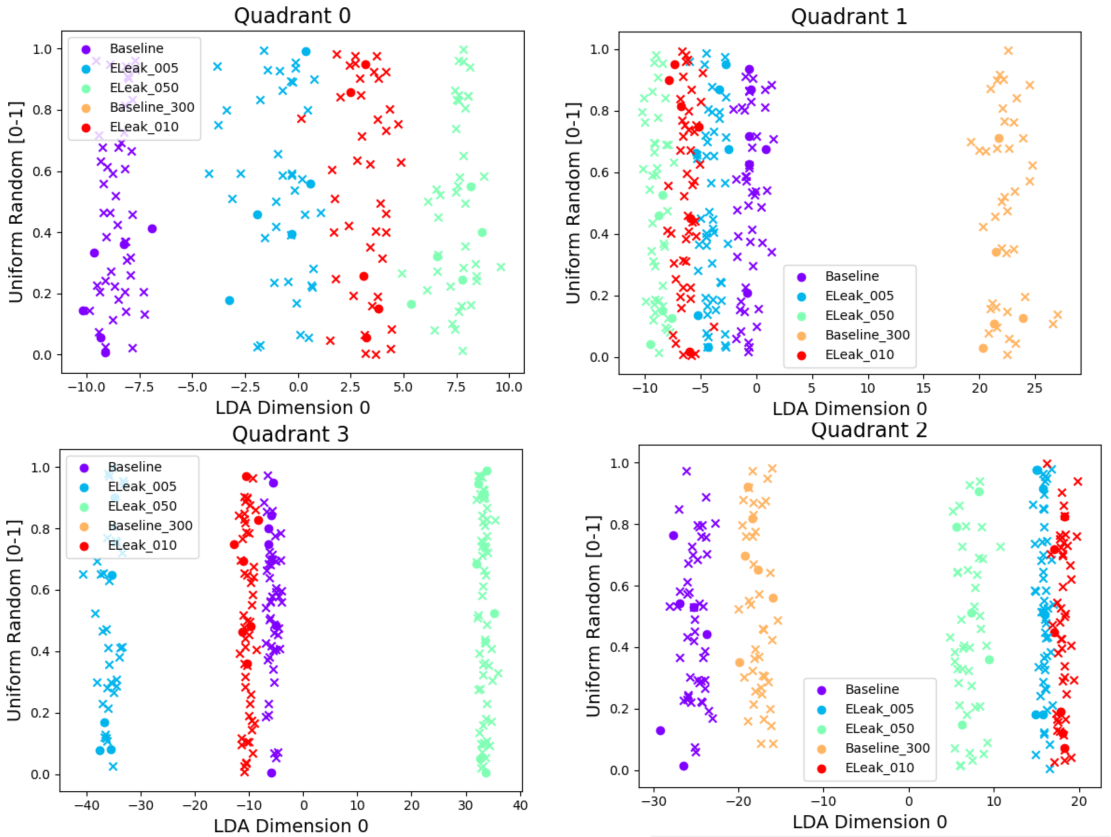
LDA on all Quadrants?

LDA 2D projection over all 4 quadrants at once yields a messy/tangled down-projection.

LDA on Quadrants | **Different Direction Unit Projection Vectors**

Dot Product of LDA Projection Vectors between Quadrants



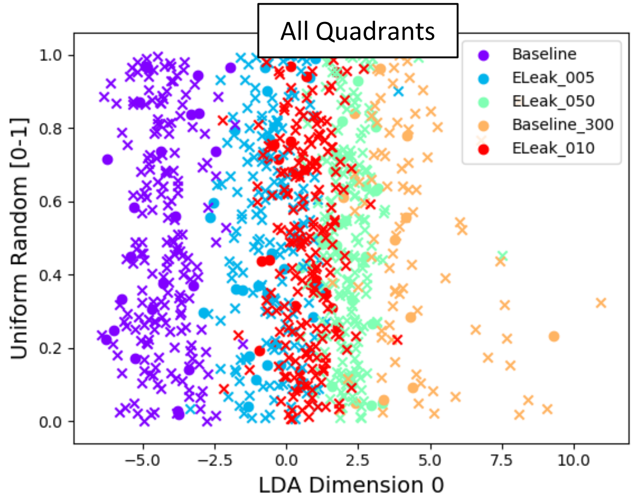


Varied Ordering

The ordering of the damage severities changes between quadrants.

This may be because a (different)particular ordering better separates the damage type groups for each quadrant, and because LDA does not try to preserve any relationship between the groups' means.

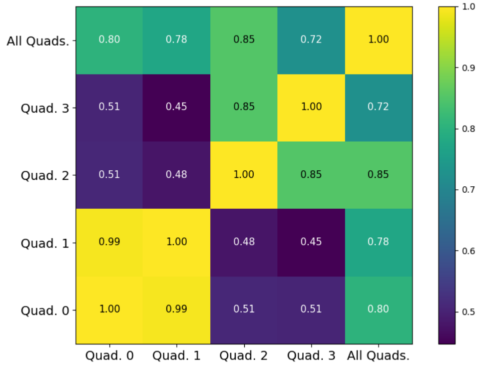
Above: Quadrants 1 and 0 have very similar directions for their projection in LDA, but the other quadrants don't have much in common. In particular, Q3 with Q0 and Q1 and Q2 with Q0 and Q1 are quite different: meaning that the ideal dimension along which the damage types are separated is not the same for each quadrant.

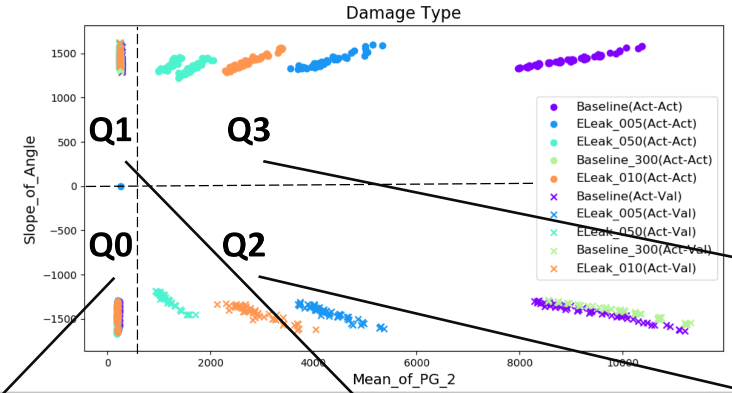


Feature Name	Weight
Var_of_Accel_1:	0.01
Var_of_Accel_2:	0.01
Var_of_Accel_3:	0.01
Mean_of_PG_1:	-0.52
Mean_of_PG_2:	-0.61
Var_of_PG_1:	-0.08
Var_of_PG_2:	-0.01
Slope_of_Angle:	-0.0
Pressure_Diff_Sum:	0.59
Pressure_Max:	0.01

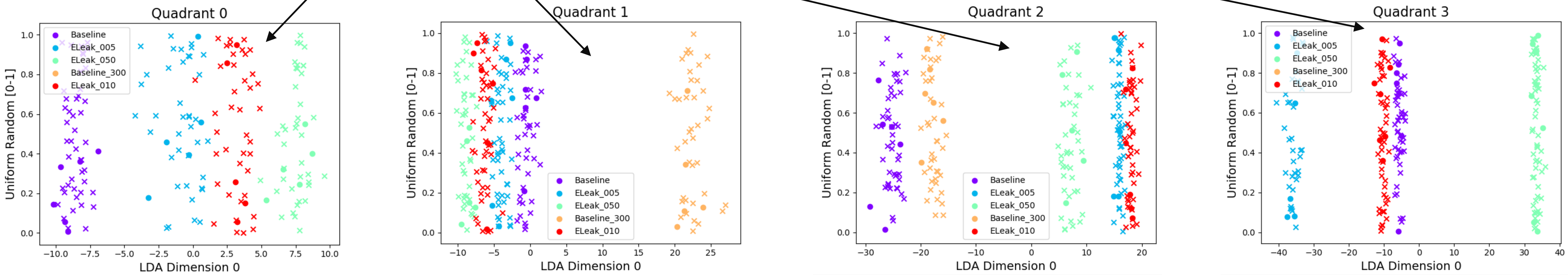
Left: A single-dimension LDA projection can separate the damage types to a reasonable extent, but the overlap appears worse than when the quadrants are treated separately (e.g. the overlap between Eleak 050 and Eleak 010 is much worse, and the overlap between Baseline_300 and Eleak_050 is worse)

LDA on Quadrants | **Projection Directions on Normalized [0-1] Features**





Different quadrants of the feature space use different measurements to best separate the damage types; e.g. Quadrants 0 and 1 use Mean of PG1, while Quadrants 2 and 3 use Mean of PG2. Quadrant 3 also uses pressure max, which none of the other quadrants use.



Quadrant 0

Var_of_Accel_1:	0.01
Var_of_Accel_2:	-0.01
Var_of_Accel_3:	-0.01
Mean_of_PG_1:	**-0.7**
Mean_of_PG_2:	-0.03
Var_of_PG_1:	-0.01
Var_of_PG_2:	0.0
Slope_of_Angle:	-0.02
Pressure_Diff_Sum:	**0.71**
Pressure_Max:	-0.0

Quadrant 1

Var_of_Accel_1:	-0.0
Var_of_Accel_2:	-0.0
Var_of_Accel_3:	0.0
Mean_of_PG_1:	**-0.69**
Mean_of_PG_2:	0.02
Var_of_PG_1:	-0.07
Var_of_PG_2:	-0.0
Slope_of_Angle:	-0.05
Pressure_Diff_Sum:	**0.71**
Pressure_Max:	0.08

Quadrant 2

Var_of_Accel_1:	-0.0
Var_of_Accel_2:	0.0
Var_of_Accel_3:	-0.0
Mean_of_PG_1:	-0.01
Mean_of_PG_2:	**-0.73**
Var_of_PG_1:	0.02
Var_of_PG_2:	-0.02
Slope_of_Angle:	-0.0
Pressure_Diff_Sum:	**0.68**
Pressure_Max:	0.04

Quadrant 3

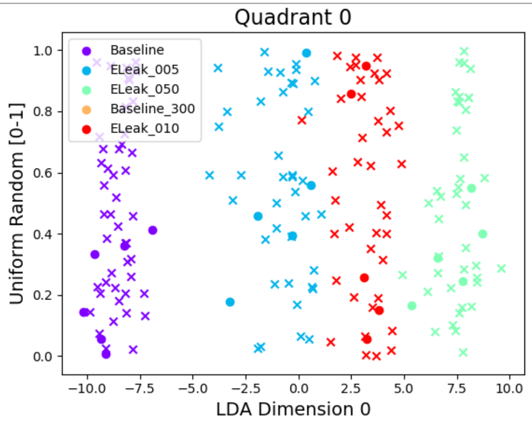
Var_of_Accel_1:	-0.01
Var_of_Accel_2:	0.0
Var_of_Accel_3:	0.0
Mean_of_PG_1:	0.04
Mean_of_PG_2:	**-0.52**
Var_of_PG_1:	-0.03
Var_of_PG_2:	0.15
Slope_of_Angle:	0.04
Pressure_Diff_Sum:	**0.72**
Pressure_Max:	**-0.42**

Subset Scores | **MHL for Each Quadrant Individually**

Using (3, 4, 8, 9)*****, a median of **1.0** for 9-fold cross validation was obtained for all 4 quadrants using the Mahalanobis Ensemble. The case wherein the slope of the angle is exactly 0 is presumed to be erroneous and discarded. In addition to these four sensors, 7 (angle of slope) was used to divide the data into the four quadrants in feature space.

**** Pressure gauge 1's mean, pressure gauge 2's mean, pressure difference sum, and pressure max)***

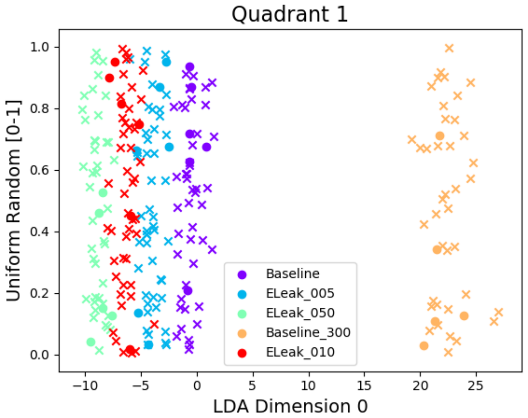
Using **just** (3, 8), median of **0.952**



Quadrant 0

Var_of_Accel_1:	0.01
Var_of_Accel_2:	-0.01
Var_of_Accel_3:	-0.01
Mean_of_PG_1:	**-0.7**
Mean_of_PG_2:	-0.03
Var_of_PG_1:	-0.01
Var_of_PG_2:	0.0
Slope_of_Angle:	-0.02
Pressure_Diff_Sum:	**0.71**
Pressure_Max:	-0.0

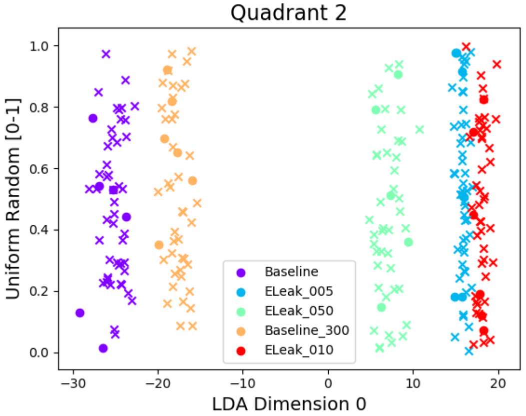
Using **just** (3, 8), median of **0.926**



Quadrant 1

Var_of_Accel_1:	-0.0
Var_of_Accel_2:	-0.0
Var_of_Accel_3:	0.0
Mean_of_PG_1:	**-0.69**
Mean_of_PG_2:	0.02
Var_of_PG_1:	-0.07
Var_of_PG_2:	-0.0
Slope_of_Angle:	-0.05
Pressure_Diff_Sum:	**0.71**
Pressure_Max:	0.08

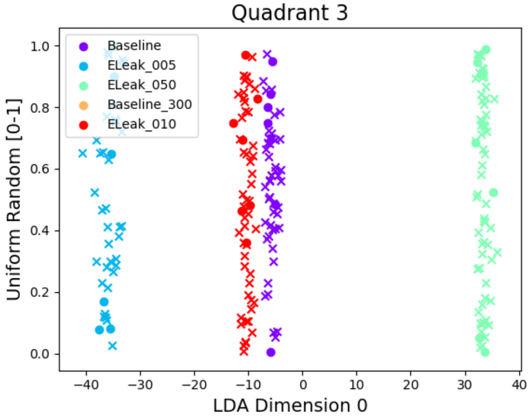
Using **just** (4, 8), median of **1.0**



Quadrant 2

Var_of_Accel_1:	-0.0
Var_of_Accel_2:	0.0
Var_of_Accel_3:	-0.0
Mean_of_PG_1:	-0.01
Mean_of_PG_2:	**-0.73**
Var_of_PG_1:	0.02
Var_of_PG_2:	-0.02
Slope_of_Angle:	-0.0
Pressure_Diff_Sum:	**0.68**
Pressure_Max:	0.04

Using **just** (4, 8), median of **1.0**



Quadrant 3

Var_of_Accel_1:	-0.01
Var_of_Accel_2:	0.0
Var_of_Accel_3:	0.0
Mean_of_PG_1:	0.04
Mean_of_PG_2:	**-0.52**
Var_of_PG_1:	-0.03
Var_of_PG_2:	0.15
Slope_of_Angle:	0.04
Pressure_Diff_Sum:	**0.72**
Pressure_Max:	**-0.42**

To confirm the earlier LDA result, the same test as above (done for damage types) was done with actuator types –any feature/sensor could be used to obtain a near perfect score in predicting whether the data came from act-act or act-val.

Summary

ACT-ACT vs ACT-VAL | LDA 1D Unit Projection Vector

LDA Projection Direction Unit Vector [9th fold]

Feature Name	Weight
Var_of_Accel_1	-0.002
Var_of_Accel_2	-0.001
Var_of_Accel_3	-0.001
Mean_of_PG_1	**-0.596**
Mean_of_PG_2	**-0.580**
Var_of_PG_1	0.053
Var_of_PG_2	0.012
Slope_of_Angle	0.004
Pressure_Diff_Sum	**0.552**
Pressure_Max	-0.006

DAMAGE TYPE | LDA 1D Unit Projection Vector

LDA Projection Direction Unit Vector [1st fold]

Feature Name	Weight
Var_of_Accel_1:	0.01
Var_of_Accel_2:	0.01
Var_of_Accel_3:	0.01
Mean_of_PG_1:	-0.52
Mean_of_PG_2:	-0.61
Var_of_PG_1:	-0.08
Var_of_PG_2:	-0.01
Slope_of_Angle:	-0.0
Pressure_Diff_Sum:	0.59
Pressure_Max:	0.01

Classification Results Summary

Using Slope of Angle and Mean of PG2 to divide the region into quadrants (tree shown on previous slide), Act-Act and Act-Val in the training & testing set are separated with **100%** accuracy.

Using the aforementioned quadrants, the Mahalanobis ensemble achieves a median of **100%** (mean appx. **98%**) accuracy on the testing set over 9-Fold stratified cross validation using just pressure gauge 1's mean, pressure gauge 2's mean, pressure difference sum, and pressure max.

Without using the quadrants above, the Random Forest (10 trees max depth of 12) achieves **98%** median accuracy using just mean of PG2, slope of angle, and the pressure difference sum.

DAMAGE TYPE | LDA 1D Projection Unit Vector for each Quadrant

Quadrants are defined by PG2's mean </> 500 and Slope of Angle </> 0.
Exactly which quadrants correspond to which regions is shown on slide 16.

Quadrant 0

Feature Name	Weight
Var_of_Accel_1:	0.01
Var_of_Accel_2:	-0.01
Var_of_Accel_3:	-0.01
Mean_of_PG_1:	**-0.7**
Mean_of_PG_2:	-0.03
Var_of_PG_1: -0.01	
Var_of_PG_2: 0.0	
Slope_of_Angle:	-0.02
Pressure_Diff_Sum:	**0.71**
Pressure_Max:	-0.0

Quadrant 1

Feature Name	Weight
Var_of_Accel_1:	-0.0
Var_of_Accel_2:	-0.0
Var_of_Accel_3:	0.0
Mean_of_PG_1:	**-0.69**
Mean_of_PG_2:	0.02
Var_of_PG_1: -0.07	
Var_of_PG_2: -0.0	
Slope_of_Angle:	-0.05
Pressure_Diff_Sum:	**0.71**
Pressure_Max:	0.08

Quadrant 2

Feature Name	Weight
Var_of_Accel_1:	-0.0
Var_of_Accel_2:	0.0
Var_of_Accel_3:	-0.0
Mean_of_PG_1:	-0.01
Mean_of_PG_2:	**-0.73**
Var_of_PG_1: 0.02	
Var_of_PG_2: -0.02	
Slope_of_Angle:	-0.0
Pressure_Diff_Sum:	**0.68**
Pressure_Max:	0.04

Quadrant 3

Feature Name	Weight
Var_of_Accel_1:	-0.01
Var_of_Accel_2:	0.0
Var_of_Accel_3:	0.0
Mean_of_PG_1:	0.04
Mean_of_PG_2:	**-0.52**
Var_of_PG_1: -0.03	
Var_of_PG_2: 0.15	
Slope_of_Angle:	0.04
Pressure_Diff_Sum:	**0.72**
Pressure_Max:	**-0.42**

ACT-ACT vs. ACT-VAL has no 1D-Projection unit vector for each quadrant because each quadrant already contains only one of Act-Act or Act-Val; no further separation is needed.